Siloed Knowledge, Siloed Tools:
Structural Barriers and Utility Costs in the Separation Between AI and Global Health Research

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In today's world, it is nearly impossible to go an entire day without hearing about, let alone interacting with, Artificial Intelligence (AI). From our reliance on AI-embedded smartphones to the growing presence of AI chatbots on numerous websites and services, AI is increasingly shaping how individuals navigate their daily lives. Unsurprisingly, its influence extends well beyond the micro level. AI is now a presence in economic systems, governance and even political movements. Global health is no exception. In this vein, the use of AI in global health raises the question of whether the individuals advancing global health research are the same ones who are developing AI systems. While some overlap exists, most activity occurs in distinctly separate spaces. Technology companies and private industry largely drive AI research and development (R&D). In contrast, global health research remains primarily situated within epistemic communities, often rooted in public-sector and academic institutions.[1] This framing illustrates the siloization of AI and global health research, leading to the research question this paper seeks to answer: How does the siloization of AI and global health research impact AI's utility for global health solutions?

This paper aims to contribute to the checks and balances necessary to ensure that AI technological advancements serve people equitably and responsibly. It does so by arguing that the structural siloization of industry-led AI R&D and global health research, conducted by epistemic communities, driven by the factors of unequal funding, talent migration, and problematic data systems, undermines trust, equity, and the practical utility of AI in global health. Bridging this divide requires integrating AI innovation within open, publicly accountable research ecosystems that support interdisciplinary collaboration and equitable data sharing.

[1] Stryker, Cole, and Eda Kavlakoglu, "What Is Artificial Intelligence (AI)?" *IBM Think*, Accessed November 10 2025, https://www.ibm.com/think/topics/artificial-intelligence.

The primary method of information gathering for this research was a literature review conducted in October 2025. Before presenting the literature review and subsequent analysis, the paper will first define key terms and concepts that provide a foundation for the following sections. In Part 1, the paper will examine three core factors identified in the literature as driving siloization. This will be followed by Part 2, an analysis of how these factors shape trust and equity, two essential considerations when evaluating the utility of AI in global health. Part 3 will follow to show what policy organizations are currently doing to address the issue. The paper will conclude with a case study of AI for AMR in Africa to contextualize the theoretical aspects discussed above, including contextually relevant policy implications, and identification of remaining knowledge gaps.

Literature Review Search Strategy

A systematic literature search was conducted in October 2025 across MacOdrum Library databases, Google Scholar, Scopus, and grey literature sources. [2] Terms related to AI, global health, siloization, and AMR were used with peer-reviewed studies, recent grey literature (2021–present), and reports/policy papers from governments and international organizations being included. Older materials were retained only when essential for context. Searches were documented, screened for rigor and relevance with both qualitative and quantitative materials included. In November 2025, a supplemental, targeted search using Google Scholar and MacOdrum Library was conducted to support the African-focused AMR case study.

[2] Documented search results and further details on search strategy see Appendix A.

Defining Concepts Important in Framing the Issue

Given the variability of definitions in this field, it is important to define the concepts on which the arguments are based. AI is the ability of computer systems to mimic human intelligence through the performance of complex tasks such as reasoning, decision-making, creating, etc.[3] Most contemporary AI systems rely on generative, adaptive, or deep learning methods that allow them to learn directly from data rather than relying on rules defined by human experts.[4] It is important to remember that AI is a technology created with social, political and economic influences and is therefore inherently not neutral or objective.[5] AI tools are developed using massive amounts of data, meaning that the quality of the data, including its bias and representativeness, directly influences the real-world effectiveness of the resulting systems and tools. With this in mind, AI solutions for global health have been framed as potentially transformative yet structurally constrained, as AI's capabilities are limited by the quality of the available data and the strength of the public health system it is intended for. According to the World Health Organization (WHO) *Ethics and Governance of Artificial Intelligence for Health* (2021), AI has the potential to strengthen health systems and expand access to care, particularly in low-resource settings, if it is developed and governed in ways that ensure equity, transparency, and accountability.[6]

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[3] National Aeronautics and Space Administration, "What Is Artificial Intelligence?" May 13 2024, https://www.nasa.gov/what-is-artificial-intelligence/.

[4] Srivastava, Divya, "AI: A Use Case for Global Health," *LSE Public Policy Review* 3, no. 3 (2024): 2.

[5] Lanyi Yu and Xiaomei Zhai, "Use of Artificial Intelligence to Address Health Disparities in Low- and Middle-Income Countries: A Thematic Analysis of Ethical Issues," *Public Health* 234 (2024): 81.

[6] World Health Organization, "Ethics and Governance of Artificial Intelligence for Health: WHO Guidance," Geneva: World Health Organization, 2021, Accessed November 1 2025, https://www.who.int/publications/i/item/9789240029200.

Siloization is defined as the "process of isolating groups, data, or departments in a way that hinders communication and cooperation between them."[7] As noted above, AI R&D is being conducted primarily by industry-led technology companies. Illustrating the growing dominance of private firms in AI research, Google, Microsoft, and Meta contributed more than double the number of accepted papers compared to the top academic institution at NeurIPS 2022.[8] This shift has created an industry-led AI R&D silo, where research is often driven by corporate priorities rather than open, public scientific inquiry.[9]

In contrast, global health, the area of research committed to the study and practice of prioritizing improving health and equity for people worldwide, is largely driven by epistemic communities, often funded by academic institutions and the public sector.[10] In global health, epistemic communities function as networks of experts who share norms, evidence standards, and policy goals that guide international health decision-making; however, critiques have observed how epistemic communities have prioritized institutional expertise over regional voices, particularly in low- and middle-income countries (LMIC).[11] While cross-sector collaboration occurs through initiatives like the OECD[12] and WHO platforms, these exchanges remain insufficient to bridge

[7] Merriam-Webster, "Silo," *Merriam-Webster.com Dictionary*, Accessed November 1, 2025. https://www.merriam-webster.com/dictionary/silo

[8] Roman Jurowetzki, Sebastian T. Scherdin, Marianne Starzer, Ole Teuteberg, and Keyvan Vakili, "The Private Sector Is Hoarding AI Researchers: What Implications for Science?" *AI & Society* (2024): 4146.

[9] Nur Ahmed, Muntasir Wahed, and Neil C. Thompson, "The Growing Influence of Industry in AI Research," *Science* 379, no. 6635 (2023): 885.

[10] Rutgers Global Health Institute, "What Is Global Health?" Rutgers Global Health Institute, Accessed October 28, 2025, https://globalhealth.rutgers.edu/what-we-do/what-is-global-health.

[11] Adebisi, Yusuff Adebayo, "Decolonizing Epidemiological Research: A Critical Perspective," *Avicenna Journal of Medicine* 13, no. 2 (2023): 71.

[12] Divya, "Use Case for Global Health," 4: "The OECD AI expert group in health is an international collaborative platform to build on existing understanding across countries working on AI and bringing in the health-specific requirements to support a proactive policy space informed by evidence and underpinned by cross-country learnings."

the entrenched divide between industry-driven AI development and epistemic communities focused on global health.

Part 1: Factors Perpetuating Siloization

The next section will elaborate on the factors which the literature review has identified as perpetuating the siloization of AI and global health research.

(1) Funding Asymmetry

In 2021, the United States (US) government allocated $1.5 billion USD, and the European Commission reserved $1.2 billion USD for non-defense AI spending.[13] In the same year, industry and the private sector invested more than $340 billion USD in AI.[14] To contextualize how great this public-private investment disparity is, research funding over the past decades for the pharmaceutical industry has roughly been divided evenly between the private and public sectors.[15] The AI funding stream is further narrowed by the fact that over 90% of funding for AI startups comes from either the US or China.[16] A significant amount of this funding originates from a small number of technology giants, such as Google, IBM and Microsoft. Together, these figures demonstrate the overwhelming concentration of AI R&D momentum within the private sector.

[13] Ahmed, "Influence of Industry," 884.
[14] Ahmed, "Influence of Industry," 884.
[15] Ahmed, "Influence of Industry," 884.
[16] Kenneth P. Seastedt, "Global healthcare fairness: We should be sharing more, not less, data" *PLOS Digital Health*, 1:10 (2022): 8.

At the same time as the seemingly endless stream of funding for AI R&D, the global health community is facing significant financial constraints. The recent shift in US foreign aid policy has left the WHO with an anticipated $1.7 billion USD budget gap for 2026-2027.[17] This is in addition to the dismantling of USAID and the overall 67% drop in spending on development assistance for health of.[18] The devastating impacts of these cuts are going to be felt disproportionately by specific LMICs.[19] While the funding will most directly impact the delivery of health assistance and programming, it will also limit the pool of available funds for global health research.

The deep but narrow funding of AI R&D has a significant influence on which technologies are being developed for, and why. If global health research is outpaced by the current flood of AI investment, the resulting imbalance risks reinforcing inequities. Thus, leaving LMICs dependent on externally designed tools that may not reflect their health priorities, data realities, or regulatory needs.

(2) The Academia-to-Industry Brain Drain

The second factor perpetuating the siloization is an academic-to-industry "brain drain" that is occurring across many STEM fields[20] disciplines, but is particularly evident in the AI R&D space. This phenomenon occurs when researchers leave roles in academia, once considered the

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[17] Clancy, Dawn, "The WHO Has to Close a Billion-Dollar Gap. Can Private Funding Help?" *Swissinfo*, July 21, 2025, https://www.swissinfo.ch/eng/geneva-organisations/the-who-has-to-close-a-billion-dollar-gap-can-private-funding-help/89695552.

[18] Loveluck, Louisa, "State of Global Health Funding — August 2025." *Think Global Health*, August 2025, https://www.thinkglobalhealth.org/article/state-global-health-funding-august-2025.

[19] Loveluck, "Health Funding."

[20] Science, Technology, Engineering, and Mathematics.

most prestigious positions, to more lucrative opportunities within industry.[21] For instance, prior to 2014, the majority of major machine learning models were developed and released by academic institutions; however, since then, industry players have increasingly taken the lead.[22]

Recent evidence shows that the private sector increasingly recruits high-impact academic researchers, those with high citation counts within established domains, while showing less interest in novel or exploratory research.[23] This "cherry-picking" of academic talent has elevated the industry's research visibility, with industry researchers tending to receive twice as many citations while publishing less.[24]

Research by Jurowetzki et al. (2025) highlights several key concerns arising from the brain drain phenomenon, three of which are directly relevant to global health. First, the financial incentives and compensation schemes common in industry may favour work with immediate applications and commercial potential.[25] As a result, AI health tools suited to LMICs, where purchasing power is limited, may be overlooked, mirroring the market failures that have long driven underinvestment in diagnostics and treatments for neglected diseases.[26] Second, private sector goals often diverge from societal priorities and may overlook the broader socio-economic consequences of technological innovation.[27] Thirdly, the private sector has not always prioritized integrating robust safety measures and guardrails into its technologies to protect users' privacy

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[21] Andreopoulos Spyros, "The Unhealthy Alliance between Academia and Corporate America," *Western Journal of Medicine* 175, no. 4 (October 2001): 225.
[22] Jurowetzki, "Private Researchers," 4146.
[23] Jurowetzki, "Private Researchers," 4147.
[24] Jurowetzki, "Private Researchers," 4147.
[25] Jurowetzki, "Private Researchers," 4147.
[26] Leah Shipton and Lucia Vitale, "Artificial Intelligence and the Politics of Avoidance in Global Health," *Social Science & Medicine* 359 (2024): 3.
[27] Jurowetzki, "Private Researchers," 4147.

and safety.[28] This is particularly important for large AI models using generative AI for health, as the consequences of misuse and or misinformation can be devastating. These risks are amplified in LMIC, where weakened public health systems may increase reliance on newly available tools, while stringent and enforceable regulatory frameworks to ensure those tools function as intended are often lacking.[29]

As the brain drain continues, the STEM community is also seeing more industry-academia funding collaborations. While beneficial in funding sources, these collaborations raise questions on the ability of academia to fulfill its traditional role of independent evaluator and ethical counterbalance to private sector influence.[30] Such partnerships risk blurring the boundaries between public scholarship and corporate interest. For example, a *Novartis*–University of California deal illustrates this tension. Even the appearance of conflict can erode public trust in the independence and integrity of academic research; however, in this collaboration, *Novartis* representatives sit on governance boards and hold rights to a share of discoveries.[31]

(3) Problematic Data: Non-Open Source and Proprietary Systems

As discussed above, AI tools require large amounts of data to be properly trained. When considering the siloization of industry-led AI and epistemic communities in global health, it is essential to understand what data is being used and who owns it. The private sector has access to large, current, proprietary datasets, as their operations often produce an ongoing consumer

[28] Jurowetzki, "Private Researchers," 4147.
[29] Shipton, "Politics of Avoidance," 3-4.
[30] Jurowetzki, "Private Researchers," 4151.
31 Andreopoulos, "Corporate America," 225.

relationship in which data is continually reported back from devices and user interactions.[32] These large datasets also translate into larger AI models capable of processing larger amounts of data. In 2021, for example, the average industry model was roughly 29 times larger than its academic counterpart, underscoring the disparity in computational power between the two sectors.[33] In contrast, those in the global health epistemic community, with public sector and academic affiliations, are often reliant on open-source datasets, which are limited in size and how static they can be.[34] Although an increase in funding would help public research institutions with their competitive edge, there remains large inefficiency concerns if these institutions were to try to replicate industry datasets and model capacities already in existence.[35]

The value of the data itself also plays a role in furthering the divide between industry and public research institutions. While many are concerned as to whether LMIC populations will be adequately considered in the development of AI tools for global health, an equally serious concern arises from the opposite problem. As Zuboff (2018) explains, the commercial value of proprietary data is central to surveillance capitalism, which "transforms private human experience—which previously existed outside the market—into a commodity that can be bought and sold as behavioural data."[36] This commercial incentive, absent in public research institutions, may increasingly drive technology companies to target LMICs with weak regulatory controls for their untapped data.[37] As noted above, even when LMICs provide the data used to develop AI tools, they are unlikely to benefit from them in the absence of a commercial incentive. Without

[32] Ahmed, "Influence of Industry," 884.
[33] Ahmed, "Influence of Industry," 884.
[34] Jurowetzki, "Private Researchers," 4145.
[35] Jurowetzki, "Private Researchers," 4145
[36] Shoshana Zuboff, "The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power" (New York: Public Affairs, 2019), 8.
[37] Shipton, "Politics of Avoidance," 4.

robust and enforceable regulatory frameworks, such practices risk reproducing historical patterns of extractive health interventions, deepening data and power inequalities between those who control data and those who merely supply it.

As AI R&D becomes dominated by those controlling proprietary data, a two-tiered research ecosystem emerges in which global health researchers operate in constrained data environments, limiting their ability to influence AI R&D.

Part 2: The Impact of Siloization on the Utility of AI in Global Health

It is rarely disputed that AI technologies have the capacity to address significant global challenges. What remains contested is the extent to which these technologies can actually deliver on that promise. The following section analyzes how the siloization described above shapes the utility of AI for global health. The focus will be on trust and equity, themes noted throughout the literature, as two critical determinants of AI's utility in this context.

(1) Trust In Artificial Intelligence

In the era of rapid technological advancements, how useful and user-friendly a technology is is important for its adoption. That being said, one of the most critical factors in determining a technology's uptake is trust in the technology and its provider.[38] The success of AI solutions, especially in times of crisis, depends less on their technological sophistication and more on the level of trust the public holds for them.[39] There is no one accepted definition of trust; however,

[38]Sage Kelly, Sherrie-Anne Kaye, and Oscar Oviedo-Trespalacios, "What factors contribute to the acceptance of artificial intelligence? A systematic review," *Telematics and Informatics* 77 (2023): 3.
[39] Kelly, "Acceptance of AI," 3.

for the purposes of this paper, trust in technology will be understood to be "the attitude that a [technology] will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability."[40] In regard to AI, this means having confidence that the system will perform as intended, make decisions transparently and fairly, and not expose users to undue risk or harm despite the complexity or opacity of its underlying processes.[41] This definition of trust is then broken down and examined in light of how siloization affects each of its constituent parts, opacity, reliability, and accountability. The next paragraphs first explore how AI relates to these trust components and then how siloization between AI and global health shapes those dynamics.

<u>Opacity:</u> The processing speeds of AI technologies are so fast and complex that it is impossible for humans to have a complete understanding of the process.[42] For this reason, many AI models are labelled as "black box" or epistemically opaque. The use of epistemically opaque tools in research is common but requires an ability to trust the decision-maker behind the tool.[43] Unfortunately, when it comes to AI tools, they are opaque not only to the users but also to the developers.[44] Therefore, the historical method of reducing the opacity of new technology is not available. This then limits the ability to verify or contest the reasoning behind AI outputs, thus challenging the foundation of trust necessary for its use. The silos between industry-led AI and epistemic global health communities further these concerns as limited access to proprietary data, models, and decision-making processes prevents independent validation and oversight.

[40] Jie Xu, Kim Le, Annika Deitermann, and Enid N H Montague, "How different types of users develop trust in technology: A qualitative analysis of the antecedents of active and passive user trust in a shared technology" *Applied Ergonomics* 45:6 (2014): 1495.
[41] Lee, John D., and Katrina A., "Trust in Automation: Designing for Appropriate Reliance," *Human Factors*, 46 no. 1 (2004): 50–80.
[42] Inkeri Koskinen, "We Have No Satisfactory Social Epistemology of AI-Based Science," *Social Epistemology*, 38:4 (2024): 458.
[43] Koskinen, "Social Epistemology," 464.
[44] Koskinen, "Social Epistemology," 464.

Reliability: Reliance is a necessary component of trust.[45] For AI to be trusted, it must reliably produce accurate and useful outputs. Remembering that, while AI is not a simple algorithm, it is still only as good as the data it is trained upon. Therefore, the reliability of an AI tool is intimately tied to the quality of the data available to the developers. As discussed, the AI-industry silo contains large proprietary datasets, while public-sector and academic researchers often operate with more limited open-source data. This imbalance not only affects model quality but also erodes the reliability necessary for trust, as it limits external validation and may result in systems that perform inconsistently across different global health contexts.

Accountability: While opacity and reliability are essential components of trust that rely on developer-led initiatives, accountability is primarily an area of governance. Effective governance helps ensure that the anticipated benefits of AI technologies are met.[46] Frameworks for accountability must have both proactive and retroactive rules surrounding oversight and transparency mechanisms for the entire lifecycle of an AI technology.[47] The greater the legal certainty of accountability frameworks, the more trust the public should have in AI systems. While consistent, reliable governance structures are still catching up with the rapid expansion of AI technologies, several key initiatives now demonstrate meaningful progress. For example, the OECD *AI Principles*, the European Union's (EU) *Artificial Intelligence Act*, and UNESCO[48] *Recommendations on the Ethics of Artificial Intelligence* provide guidance on oversight aimed at

[45] Hosseini Shoabjareh, Azamsadat, Milad Ghasri, Tom Roberts, Andrew Lapworth, Ned Dobos, and Christine Boshuijzen-van Burken, "The Role of Trust and Distrust in Technology Usage: An In-Depth Investigation of Traffic Information Apps Usage for Mandatory and Non-Mandatory Trips," *Travel Behaviour and Society* 37 (2024): 2.
[46] Claudio Novelli, Mariarosaria Taddeo, and Luciano Floridi, "Accountability in artificial intelligence: what it is and how it works," *AI &* Society, 39 (2024): 1880.
[47] Novelli, "Accountability," 1879-1880.
[48] United Nations Educational, Scientific and Cultural Organization.

building public trust in AI.[49] Until legally enforceable standards exist and are applied internationally, the siloed development of AI away from global health research will produce uneven accountability, widening governance gaps, and undermining the trust needed for equitable and ethical integration of AI into global health systems.

(2) Equity: Bias and Fairness

Bias is another important lens to analyze how siloization affects the utility of AI in global health. Bias can shape who benefits from technologies, from whose data informs development to how equitably its outcomes are distributed.

Algorithmic bias is when an AI technology produces unfair or incorrect outcomes due to human bias embedded in the data or the algorithm's design.[50] The intentional inclusion of algorithmic bias in an AI tool is considered a prohibited practice and carries significant penalties. For example, uunder the EU *AI Act*, non-compliance with prohibited practices can result in fines of up to 35 million euros.[51] Because of the awareness of this algorithmic bias and the deterrents in place for it, the more significant concern lies in unintentional contextual bias. This occurs when AI technologies are developed and trained using datasets not representative of all people who could benefit or may use the tool.[52] Most often this means AI trained on datasets of high income countries (HIC), which introduces biases into the model that then leads to poor performance or

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[49] Organisation for Economic Co-operation and Development, "AI Principles," OECD. https://www.oecd.org/en/topics/sub-issues/ai-principles.html; European Union, "Regulation (EU) 2024/1689 of the European Parliament and of the Council on artificial intelligence (Artificial Intelligence Act)," Official Journal of the European Union, https://artificialintelligenceact.eu/; UNESCO, "Recommendation on the Ethics of Artificial Intelligence," Paris: UNESCO, 2021, https://www.unesco.org/en/artificial-intelligence/recommendation-ethics.
[50] Jonker, Alexandra, and Julie Rogers, "What Is Algorithmic Bias?" *IBM Think*, Accessed October 28 2025, https://www.ibm.com/think/topics/algorithmic-bias.
[51] Jonker, "Algorithmic Bias".
[52] Shipton, "Politics of Avoidance," 6.

inaccurate results in LMIC.[53] This is particularly harmful in the health context, where mistakes can result in life or death consequences.

While concerns about the scale at which data from HICs may be applied in LMICs are critically important, it is not the only type of unintentional bias. For example, women in LMIC are less likely to have access to mobile devices and the internet and are therefore even more underrepresented in data.[54] Siloization further exacerbates these biases as industry-led AI R&D often prioritizes markets with commercial incentives.[55] When financial motivations dictate research priorities, the resulting technologies reinforce existing inequities rather than addressing global health needs.

Having looked at the impacts on global health of biased AI models trained on HIC data and used in LMIC, there is a reverse dynamic to consider. That is to say, when data from LMICs is used to develop AI tools intended primarily for use in HIC contexts. This approach is also known as ethical dumping, whereby technology companies collect data from populations in a manner that would not be permitted in other regulatory settings.[56] These unethical practices are usually conducted at the expense of vulnerable populations.[57] While being pawns in the corporate strategy, these populations rarely see the benefits from the tools their data helped develop.[58]

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[53] Jenny Yang et al., "Mitigating machine learning bias between high income and low–middle income countries for enhanced model fairness and generalizability," *Scientific Reports*, 14 (2024): 1.
[54] Lanyi Yu, and Xiaomei Zhai, "Use of artificial intelligence to address health disparities in low- and middle-income countries: a thematic analysis of ethical issues," *Public Health,* 234 (2024): 81.
[55] Bryan, Kevin A., and Florenta Teodoridis, "Balancing Market Innovation Incentives and Regulation in AI: Challenges and Opportunities," *Brookings Institution* (Economic Studies), September 24 2024, https://www.brookings.edu/articles/balancing-market-innovation-incentives-and-regulation-in-ai-challenges-and-opportunities/.
[56] Yu, "LMIC disparities," 82.
[57] Yu, "LMIC disparities," 78.
[58] Yu, "LMIC disparities," 82.

While financial incentives may drive some of this behaviour, this strategy is contingent on decision-makers being able to operate with limited government regulation or social accountability, as may be the case in some LMICs. To reiterate the theme observed throughout this paper, siloization amplifies these ethical concerns by concentrating AI R&D within profit-driven industry spaces that often operate apart from public oversight. This separation enables practices such as data extraction from LMICs to persist with minimal accountability, reinforcing global inequities and undermining the ethical foundations of AI in health.

Taken together, the analysis of trust and equity demonstrates that the siloization of AI and global health research not only undermines the effectiveness of AI technologies in addressing global health challenges but also erodes the foundations required for their legitimate and sustained use worldwide.

Part 3: How Policy Organizations Are Addressing the Issue

Although there has been no explicit reference to addressing siloization, several global and regional policy organizations have begun addressing the challenges created by the siloization of AI R&D and global health research. The WHO has issued guidance through WHO's *Ethics and Governance of AI for Health* (2021) and more recently, *Ethics and governance of artificial intelligence for health: Guidance on large multi-modal models* (2025).[59] These documents call for equity in AI design, transparent data governance, and accountability mechanisms suitable for

[59] World Health Organization, *Ethics and Governance of Artificial Intelligence for Health: Guidance on Large Multi-Modal Models* (Geneva: WHO, March 25 2025), https://www.who.int/publications/i/item/9789240084759; World Health Organization, *Ethics and Governance of Artificial Intelligence for Health: WHO Guidance* (Geneva: WHO, 2021), https://www.who.int/publications/i/item/9789240029200.

low-resource settings. Similarly, the OECD *AI Principles* promote transparency, safety, and responsible innovation, and provide a shared governance framework that facilitates collaboration between the technology sector and public-sector health research institutions.[60] UNESCO's *Recommendation on the Ethics of Artificial Intelligence* provides normative guidance on fairness, inclusivity, and human rights considerations, explicitly highlighting the need to provide extra consideration for vulnerable populations.[61]

Regional bodies have also taken steps to address concerns with AI in global health. The EU's *Artificial Intelligence Act* establishes legally enforceable standards for risk classification, transparency, and accountability, addressing opacity and reliability concerns that undermine trust in health-related AI systems.[62] The African Union, through its Digital Transformation Strategy (2020-2030), emphasizes the need for digital public infrastructure, interoperable health-data systems, and local capacity building.[63]

Additionally, collaborative research initiatives, such as the Fleming Initiative's partnership with Google DeepMind and African-focused data science fellowships like the Capacity Accelerator Network (CAN), indicate emerging efforts to align AI innovation with global health needs. Together, these organizations are attempting to reduce the governance, funding/capacity, and data gaps that impact siloization. Despite this optimism, coordination remains uneven, and major funding gaps persist.

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[60] Organization for Economic Co-operation and Development, "OECD AI Principles", Accessed November 18 2025, https://oecd.ai/en/ai-principles.
[61] UNESCO, *Recommendation on the Ethics of Artificial Intelligence*, (Paris: UNESCO, 2021), https://unesdoc.unesco.org/ark:/48223/pf0000381137.
[62] European Union, "Artificial Intelligence Act."
[63] African Union, *Digital Transformation Strategy for Africa 2020-2030* (Addis Ababa: African Union, 2020), https://au.int/sites/default/files/documents/38507-doc-dts-english.pdf.

Case Study: AI for AMR in Africa

Antimicrobial Resistance (AMR) is one of the most pressing global health threats. AMR is the process by which bacteria, viruses and parasites develop the ability to resist the drugs' ability to kill them.[64] In 2019, it was estimated that multidrug-resistant bacteria contributed to approximately 4.95 million deaths worldwide.[65] As with most global health concerns, the burden is unequally distributed, with sub-Saharan Africa having the highest AMR-attributable mortality rate at roughly 27 deaths per 100,000 people.[66] Without urgent intervention, global AMR deaths could reach 10 million annually by 2050.[67]

As this paper has shown, global health research and AI R&D continue to evolve within silos, industry-led AI R&D on one side and publicly funded epistemic global health communities on the other. AMR provides a particularly compelling lens through which to examine the consequences of these divisions, as it is inherently cross-disciplinary. AMR sits at the intersection of microbiology, clinical medicine, epidemiology, data science, and global governance across human, animal and environmental spaces. Yet despite its integrative nature, AMR research and AI innovation remain shaped by the same structural siloization that characterizes the broader field. The following section applies the preceding analysis to the

[64] Timothy R Walsh et al., "Antimicrobial Resistance: Addressing a Global Threat to Humanity," *PLoS Medicine,* 20:7 (2023), 1.
[65] Walsh, "AMR: Global Threat," 1.
[66] Innocent Ayesiga *et al.*, "Artificial intelligence-enhanced biosurveillance for antimicrobial resistance in sub-Saharan Africa," *International Health,* 17 (2025): 795.
[67] Walsh, "AMR: Global Threat," 1.

AMR context in Africa, identifying ways in which these silos can be bridged and interdisciplinary collaboration strengthened.

The Case for AI in Addressing AMR in Africa

AI offers a powerful opportunity to strengthen AMR control in Africa by addressing one of the region's most urgent challenges, the lack of reliable surveillance data. Because AI can support rapid detection of resistant strains, predict emerging resistance patterns, and accelerate genomic and susceptibility analyses, it has the potential to fill critical gaps. [68] Yet, this potential remains largely unrealized due to resource constraints, infrastructural gaps, and persistent data scarcity.[69] Across the continent, surveillance systems are fragmented or absent and implementation of the WHO Global Action Plan[70] for AMR is slow. As of 2022, of the 47 countries in the WHO's African region, only 15 were submitting surveillance data to the global database.[71]

This persistent data void makes it difficult to understand the true scale of resistance or to coordinate responses. [72] In this context, AI's potential is compelling not only because it brings novel technology, but because it could help close the foundational surveillance gap that hinders AMR control efforts.

[68] Ayesiga, "Biosurveillance sub-Sahharan Africa," 795.
[69] Ayesiga, "Biosurveillance sub-Sahharan Africa," 795.
[70] Nationally known as National Action Plans (NAP).
[71] Walter L Fuller *et al.,* "National action plan on antimicrobial resistance: An evaluation of implementation in the World Health Organization Africa region," *Journal of Public Health in Africa,* 13:2, (2022): 1.
[72] Obiageli Jovita Okolie, Uzoma Igwe, Sanda Umar Ismail, Uzairue Leonard Ighodalo, and Emmanuel C. Adukwu, "Systematic review of surveillance systems for AMR in Africa," *Journal of Antimicrobial Chemotherapy*, 78 (2023): 32.

Structural Factors Perpetuating AMR/AI Silos in the African Context

First, an ongoing brain drain affects both the AI and AMR research spaces. Globally, the AMR research community is limited, with an estimated 3,000 active clinical AMR researchers.[73] At the same time, AI expertise is disproportionately concentrated, as 70% of all AI R&D is located in only five countries, with sub-Saharan Africa producing the fewest peer-reviewed AI publications worldwide.[74] This unequal distribution of skilled researchers is constraining collaboration and limiting the development and deployment of AI tools tailored to African surveillance needs and health-system realities.

Second, and perhaps most significant, funding asymmetry continues to undermine AI-AMR innovation on the continent. Although most African states have drafted AMR National Action Plans, the majority remain unfunded and therefore unimplemented.[75] Declining global development assistance further restricts resources for essential AMR control components such as laboratory strengthening, workforce development, and coordinated surveillance. Many African countries, some of which spend more on debt servicing than on health, lack the fiscal space required for sustained AMR programming.[76] This is in contrast to the surge of funding being directed towards AI research, as detailed above. While mechanisms such as pooled

[73] AMR Industry Alliance*, "Leaving the Lab: Tracking the Decline in AMR R&D Professionals," (Geneva: AMR Industry Alliance, 2024),* https://www.amrindustryalliance.org/mediaroom/leaving-the-lab-tracking-the-decline-in-amr-rd-professionals.

[74] Marcopolo, "*The Global AI Talent Tracker 2.0,"* (Chicago: MacroPolo, 2023), https://archivemacropolo.org/interactive/digital-projects/the-global-ai-talent-tracker/; Ara Darzi and Anna Koivuniemi. "Harnessing Artificial Intelligence to Tackle Antimicrobial Resistance," Imperial College London (Fleming Initiative & Google DeepMind), January 16 2025, https://www.imperial.ac.uk/Stories/harnessing-artificial-intelligence-tackle-antimicrobial-resistance/.

[75] *Antimicrobial Resistance: Accelerating national and global responses*, 77th World Health Assembly, A77/5 (11 April 2024).

[76] United Nations, Office of the Special Adviser on Africa, *Unpacking Africa's Debt: Towards a Lasting and Durable Solution* (New York: United Nations, 14 November 2024), 41.

African Union AMR funds or debt-for-development swaps offer potential solutions, chronic underinvestment continues to fragment AMR control strategies and weaken national stewardship capacities.[77]

Third, the region faces profound dataset limitations and data fragmentation, which directly limit AI utility. AMR surveillance remains inconsistent, with many countries dependent on isolated laboratory-based phenotypic testing instead of national surveillance databanks.[78] Even where data systems exist, they are often siloed or controlled by proprietary holders, reproducing inequities in access to datasets.[79] These dataset constraints reinforce dependence on models trained in high-income contexts where datasets are more extensive, limiting the relevance of AI outputs for African health systems.[80]

The combined effect of these structural factors is that AI researchers, highly concentrated in a few high-income countries, are often disconnected from the realities of AMR in African settings and lack both the incentives and the accessible datasets needed to meaningfully address region-specific challenges.

[77] Darzi, "Fleming Initiative & Deep Mind."; Sherin Paul and Mirfin Mpundu, "Reimagining Antimicrobial Resistance (AMR) Financing for Africa amid Global Funding Crises," *Speaking of Medicine and Health*, (June 5, 2025), https://speakingofmedicine.plos.org/2025/06/05/reimagining-antimicrobial-resistance-amr-financing-for-africa-amid-global-funding-crises/.

[78] Okolie, "Surveillance AMR Africa," 49.

[79] Darzi, "Fleming Initiative & Deep Mind."

[80] Yu, "LMIC disparities," 82.

Trust and Equity Implications

As discussed earlier in Part 2, these structural factors undermine trust and equity, important parts of AI use. This manifests in a number of ways: incomplete and not context-relevant datasets produce biased models and unequal access to data perpetuates global health inequities.

While these dynamics matter within Africa, they exist within the deeper and more immediate capacity constraint of resources and infrastructure. These capacity gaps remain the biggest barrier to deploying AI in a trustworthy and equitable way for AMR control.

Silo Bridging Recommendations and Policy Implications

Bridging the silos of AI R&D and AMR research and control in Africa requires interventions that 1) strengthen data and tool accessibility, 2) build infrastructure that supports integration, and 3) expand interdisciplinary collaboration. The following recommendations have been identified from the literature and AMR policy space and have then been paired with the necessary policy implications.

<u>Recommendation 1:</u> Strengthen Data and Tool Accessibility

Policy Implications:

a. Prioritize the usability of AMR datasets from LMIC for AI tools. Tools should be developed that rely on data formats more available in low-resource settings, such as clinical or microbiological images, rather than assuming access to higher complexity "-

omic" datasets (ie. genomics).[81] This provides an interim solution to help bridge the gap while infrastructure capacity for more complex surveillance is developing. Tools like AntiMicro.ai[82], which repurposes Pfizer's open-source ATLAS dataset, demonstrates that when global datasets are shared and adapted, LMIC researchers can meaningfully contribute to AI-AMR solutions.[83]

b. Supporting the creation of tools that do not require stable internet connection as needed for low-resource settings. An example being *Antibiogo*[84] which runs entirely on local devices, expanding access to antibiotic susceptibility tests essential for making appropriate antimicrobial stewardship decisions.

Recommendation 2: Build Infrastructure that Supports Integration

Policy Implication: Digital governance systems must be strengthened. Investments in strong digital public infrastructure (DPI) are foundational for enabling global data exchange, proper development oversight, and trustworthy AI deployment.[85] Effective and sustainable DPI must be secure, interoperable, and built on open technologies.[86] The importance of this was cemented by the G20's 2023 Indian Presidency.[87]

Recommendation 3: Expand Interdisciplinary Collaboration

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[81] Darzi, "Fleming Initiative & Deep Mind."
[82] A Kenyan-led AI tool: Sarah Daniel, "Kenyan AI Doctor Shaping Global Action on Antimicrobial Resistance," *Ducit Blue Solutions*, (October 29 2025), https://www.ducitblue.com/kenyan-ai-doctor-shaping-global-action-on-antimicrobial-resistance/.
[83] Darzi, "Fleming Initiative & Deep Mind."
[84] Antibiogo is a tool that provides reliable and accessible antibiotic susceptibility testing: Antibiogo, "Join the fight against antimicrobial resistance," (Accessed November 5, 2025), https://www.antibiogo.org.
[85] Darzi, "Fleming Initiative & Deep Mind."
[86] Darzi, "Fleming Initiative & Deep Mind."
[87] Organisation for Economic Co-operation and Development. *Digital Public Infrastructure for Digital Governments: OECD Public Governance Policy Papers No. 68*. Paris: OECD Publishing, December 2024, 8.

Policy Implication: The declining AMR researcher workforce and growing AI investments highlight a critical gap. Stable career paths, especially in LMIC, supported by long-term funding, are needed to improve interdisciplinary collaboration for more effective solutions. Fellowships such as the CAN program for early-career African data scientists and the fully funded Fleming Initiative–DeepMind postdoctoral fellowship illustrate the type of long-term commitments needed to build regional expertise.[88]

Remaining gap: Managing incentives and safeguarding fairness

Beyond individual fellowships and training programs, stronger incentives will be needed to attract industry and private investment into the AMR space. Some have proposed the monetization of data to create priority access to shared research or surveillance resources.[89] As noted earlier, this raises significant concerns about misuse and inequitable control of health data. Given the pace of AI development, LMICs must find ways to benefit from emerging tools now while avoiding long-term risks tied to opaque or exploitative data practices. While many alarm bells have been raised about this potential harm, knowledge gaps persist on efficient and effective accountability mechanisms to address this. Further work is needed to determine accountability mechanisms that would allow LMICs to participate in and benefit from AI-AMR innovation without compromising ethical standards or sovereignty over their data.

88 Darzi, "Fleming Initiative & Deep Mind."

89 Darzi, "Fleming Initiative & Deep Mind."

Conclusion

This paper has examined how the siloization of industry-led AI research and epistemic global health research communities fundamentally limits the usefulness of AI tools needed to address global health challenges. Asymmetrical financing, academic-to-industry talent migration, and problematic data systems collectively erode trust and reinforce global inequities. The result is a concentration of AI innovation in settings disconnected from the health priorities of LMICs. AI carries great promise, including for challenges like surveillance of AMR in low-resource settings, but it can only work effectively when supported by transparent, accountable, and equitable systems. As examined in the African context, bridging the silos to help harness AI's potential will require significant investment and strong political will to create stronger digital public infrastructure, open and relevant datasets, and globally coordinated oversight. In doing so, silos may be bridged, helping ensure that AI solutions benefit all populations rather than only those with the resources to access them.

Appendix A

Literature Review Search Strategy

Table 1. Boolean and Search Operators by Database

Database / Source	Supported Boolean / Search Operators	Notes
Google Scholar	AND, OR, -, “ ”	‘AND’ implied between words; ‘-’ functions as NOT; truncation not supported
Scopus	AND, OR, NOT, “ ”, *, ?, ( )	Supports full Boolean logic, truncation, and single-character wildcards
PubMed	AND, OR, NOT, “ ”, *, [Mesh], [tiab]	Uses Boolean logic with controlled vocabulary and field tags
WHO IRIS / UN Digital Library	AND, OR, NOT, “ ”, *	Standard Boolean logic and truncation supported
MacOdrum Library	AND, OR, NOT, “ ”, *	Based on EBSCO/ProQuest standards; truncation and phrase searching supported

(Note: This table was generated using AI and verified against official databases where available.)

Search Strategy Summary

A systematic literature search was conducted in October 2025 using MacOdrum Library databases, Google Scholar, Scopus, PubMed, and grey sources. Boolean operators were applied to combine terms related to Artificial Intelligence, global health, silozation, and antimicrobial resistance (AMR). Inclusion criteria focused on peer-reviewed research, government and international organization reports, and recent grey literature (2021–present). Quantitative and qualitative studies with global scope were included. Articles predating 2021 were excluded unless offering essential context. Each search was documented and screened for methodological rigor and thematic relevance, when large numbers of search results were returned, the first 40 results were screened for relevance. Duplicates were not included if they were found in more than one search string or database/source.

In November 2025, an additional search was conducted for to focus case study on AMR to the African context. This search is documented below in the table; however, only Google Scholar and MacOdrum Library were consulted as sufficient resources were retrieved through these databases. This case study does not contain a complete literature review.

Search Strategy Documentation Table

Date of Search	Database Used	Search Terms	Total # Articles	Articles Included in Review for Paper
10/10/2025	Google Scholar	("Artificial Intelligence" OR "AI") AND ("global health" OR "One Health")	17,800	Kerasidou, A. (2021). Ethics of artificial intelligence in global health: Explainability, algorithmic bias and trust. *Journal of Oral Biology and Craniofacial Research*, *11*(4), 612-614. Murphy, K., Di Ruggiero, E., Upshur, R., Willison, D. J., Malhotra, N., Cai, J. C., & Gibson, J. (2021). Artificial intelligence for good health: a scoping review of the ethics literature. *BMC medical ethics*, *22*(1), 14. Ciecierski-Holmes, T., Singh, R., Axt, M., Brenner, S., & Barteit, S. (2022). Artificial intelligence for strengthening healthcare systems in low-and middle-income countries: a systematic scoping review. *NPJ digital medicine*, *5*(1), 162. Kaushik A, Barcellona C, Mandyam NK, Tan SY, Tromp J. Challenges and Opportunities for Data Sharing Related to Artificial Intelligence Tools in Health Care in Low- and Middle-Income Countries: Systematic Review and Case Study From Thailand. J Med Internet Res. 2025 Feb 4;27:e58338. doi: 10.2196/58338. PMID: 39903508; PMCID: PMC11836587. Hassan M, Kushniruk A, Borycki E. Barriers to and Facilitators of Artificial Intelligence Adoption in Health Care: Scoping Review. JMIR Hum Factors. 2024 Aug 29;11:e48633. doi: 10.2196/48633. PMID: 39207831; PMCID: PMC11393514.
10/10/2025	Google Scholar	("Artificial Intelligence" OR "AI") AND ("global health") AND ("integration" OR "silo")	22,900	Zhang, J., Budhdeo, S., William, W., Cerrato, P., Shuaib, H., Sood, H., ... & Teo, J. T. (2022). Moving towards vertically integrated artificial intelligence development. *NPJ digital medicine*, *5*(1), 143. Tan, T. F., Thirunavukarasu, A. J., Jin, L., Lim, J., Poh, S., Teo, Z. L., ... & Ting, D. S. W. (2023). Artificial intelligence and digital health in global eye health: opportunities and challenges. *The Lancet Global Health*, *11*(9), e1432-e1443. Samuel, G. (2024). The Ubuntu Way: Ensuring Ethical AI Integration in Health Research. *Wellcome Open Research*, *9*, 625.
10/10/2025	Google Scholar	("Artificial Intelligence" OR "AI") AND	6,620	Mohammed, A. M., Oleiwi, J. K., Osman, A. F., Adam, T., Betar, B. O., Gopinath, S. C., & Ihmedee, F. H. (2025). Enhancing antimicrobial resistance strategies: Leveraging artificial

		("global health") AND ("AMR" OR "antimicrobial resistance") AND ("integration" OR "silo")		intelligence for improved outcomes. *South African Journal of Chemical Engineering*, *51*(1), 272-286. Kasse, G. E., Cosh, S. M., Humphries, J., & Islam, M. S. (2025). Leveraging artificial intelligence for One Health: opportunities and challenges in tackling antimicrobial resistance-scoping review. *One Health Outlook*, *7*(1), 51. Ayesiga, I., Yeboah, M. O., Okoro, L. N., Edet, E. N., Gmanyami, J. M., Ovye, A., ... & Atwau, P. (2025). Artificial intelligence-enhanced biosurveillance for antimicrobial resistance in sub-Saharan Africa. *International Health*, *17*(5), 795-803. Chindelevitch, L., Jauneikaite, E., Wheeler, N. E., Allel, K., Ansiri-Asafoakaa, B. Y., Awuah, W. A., ... & van Dongen, M. (2022). Applying data technologies to combat AMR: current status, challenges, and opportunities on the way forward. *arXiv preprint arXiv:2208.04683*. Pennisi, F., Pinto, A., Ricciardi, G. E., Signorelli, C., & Gianfredi, V. (2025). The role of artificial intelligence and machine learning models in antimicrobial stewardship in public health: a narrative review. *Antibiotics*, *14*(2), 134. Howard, A., Aston, S., Gerada, A., Reza, N., Bincalar, J., Mwandumba, H., ... & Buchan, I. (2024). Antimicrobial learning systems: an implementation blueprint for artificial intelligence to tackle antimicrobial resistance. *The Lancet Digital Health*, *6*(1), e79-e86. Perrella, A., Maffettone, A., Di Micco, P., Trama, U., Bernardi, F. F., & Bisogno, M. (2025). From Guidelines to Real-Time Guardrails: The Emerging Role of AI in AMR Surveillance and IPC Decision-Making. Waldock, W. J., Thould, H., Chindelevitch, L., Croucher, N. J., de la Fuente, C., Collins, J. J., ... & Darzi, A. (2025). Mitigating antimicrobial resistance by innovative solutions in AI (MARISA): a modified James Lind Alliance analysis. *npj Antimicrobials and Resistance*, *3*(1), 75.
10/10/2025	Google Scholar	("Artificial Intelligence" OR "AI") AND ("research") AND ("silo" OR "private")	28,700	Jurowetzki, R., Hain, D.S., Wirtz, K. *et al.* The private sector is hoarding AI researchers: what implications for science?. *AI & Soc* **40**, 4145–4152 (2025). https://doi.org/10.1007/s00146-024-02171-z Ahmed, Nur, et al. "The Growing Influence of Industry in AI Research." *Science (American Association for the Advancement of Science)*, vol. 379, no. 6635, 2023, pp. 884–86, https://doi.org/10.1126/science.ade2420.
10/10/2025	Scopus	("Artificial Intelligence" OR "AI") AND ("global health") AND ("silo*")	4	

10/10/2025	Scopus	("global health") AND ("silo*")	138	Correia, Tiago, et al. “Preparing for the ‘next Pandemic’: Why We Need to Escape from Our Silos.” *The International Journal of Health Planning and Management.*, vol. 39, no. 4, 2024, pp. 973–79, https://doi.org/10.1002/hpm.3757. Kakkattil, Pradeep, et al. “Breaking the Silos: How the Health Innovation and Investment Exchange (HIEx) Helps Bridge the Health Innovation Ecosystem.” *Resilient Health : Leveraging Technology and Social Innovations to Transform Healthcare for COVID-19 Recovery and Beyond /*, Academic Press, 2024, pp. 979–87, https://doi.org/10.1016/B978-0-443-18529-8.00082-2.
10/10/2025	Scopus	("Artificial Intelligence" OR "AI") AND ("global health") AND ("AMR" OR "anti* resistance") AND ("integration" OR "silo*")	31	Singh, Samradhi, et al. “Advancing AMR Surveillance: Confluence of One Health and Big Data Integration.” *EcoHealth.*, vol. 22, no. 3, 2025, pp. 403–14, https://doi.org/10.1007/s10393-025-01724-y. Abavisani, Mohammad, et al. “Chatting with Artificial Intelligence to Combat Antibiotic Resistance: Opportunities and Challenges.” *Current Research in Biotechnology.*, vol. 7, 100197, 2024, https://doi.org/10.1016/j.crbiot.2024.100197.
10/10/2025	MacOdrum Library	("Artificial Intelligence" OR "AI") AND ("global health") AND (silo*)	5	
10/15/2025	MacOdrum Library	AI AND Health AND Silo*	197	de Graaf, Ysanne, et al. “Societal Factors Influencing the Implementation of AI-Driven Technologies In.” *PloS One*, vol. 20, no. 6, 2025, p. e0325718, https://doi.org/10.1371/journal.pone.0325718. Shoshana Zuboff, “The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power” (New York: Public Affairs, 2019), 8.

10/15/2025	MacOdrum Library	epistemic AND AI AND "Global health"	10	Morley, Jessica, et al. "Global Health in the Age of AI: Charting a Course for Ethical Implementation and Societal Benefit." *Minds and Machines (Dordrecht)*, vol. 35, no. 3, 31, 2025. Leah Shipton and Lucia Vitale, "Artificial Intelligence and the Politics of Avoidance in Global Health," *Social Science & Medicine* 359 (2024): 3.
10/15/2025	MacOdrum Library	epistemic AND AI research	1274	
10/15/2025	MacOdrum Library	epistemic AND AI research AND health	222	
10/15/2025	PubMed	("Artificial Intelligence" OR "AI") AND ("global health") AND (silo*)	22	
10/15/2025	PubMed	AI AND Health AND Silo*	157	Calvino, Giulia, et al. "Federated Learning: Breaking Down Barriers in Global Genomic Research." *Genes.*, vol. 15, no. 12, 1650, 2024, https://doi.org/10.3390/genes15121650.
10/15/2025	PubMed	epistemic AND AI AND "Global health"	6	Bhaumik S. On the ethical and moral dimensions of using artificial intelligence for evidence synthesis. PLOS Glob Public Health. 2025 Mar 19;5(3):e0004348. doi: 10.1371/journal.pgph.0004348. PMID: 40106511; PMCID: PMC11922218.
10/15/2025	PubMed	epistemic AND AI research AND health	60	
11/05/2025	Google Scholar	AMR AND AI AND Africa	22400	Essack, Sabiha, and Sabiha Y. Essack. "AMR Surveillance in Africa: Are We There Yet?." *International Journal of Infectious Diseases* 152 (2025): 107828. Ayesiga, Innocent, et al. "Artificial intelligence-enhanced biosurveillance for antimicrobial resistance in sub-Saharan Africa." *International Health* 17.5 (2025): 795-803. Okolie, Obiageli Jovita, et al. "Systematic review of surveillance systems for AMR in Africa." *Journal of Antimicrobial Chemotherapy* 78.1 (2023): 31-51. Kariuki, Samuel, et al. "Antimicrobial resistance rates and surveillance in sub-Saharan Africa: where are we now?." *Infection and drug resistance* (2022): 3589-3609.

				Adedeji, Roqeeb, et al. "Supervised Learning Model Systems to Predict and Identify Drivers of AMR in Africa." *Wellcome Open Research* 10 (2025): 410. Kasse, Gashaw Enbiyale, et al. "Leveraging artificial intelligence for One Health: opportunities and challenges in tackling antimicrobial resistance-scoping review." *One Health Outlook* 7.1 (2025): 51. Chindelevitch, Leonid, et al. "Applying data technologies to combat AMR: current status, challenges, and opportunities on the way forward." *arXiv preprint arXiv:2208.04683* (2022). Mohammed, Aeshah M., et al. "Enhancing antimicrobial resistance strategies: Leveraging artificial intelligence for improved outcomes." *South African Journal of Chemical Engineering* 51.1 (2025): 272-286. Sartorius, Benn, et al. "The burden of bacterial antimicrobial resistance in the WHO African region in 2019: a cross-country systematic analysis." *The Lancet Global Health* 12.2 (2024): e201-e216.
11/05/2025	Google Scholar	AMR AND AI AND "surveillance in Africa"	1	
11/05/2025	Google Scholar	AMR AND AI AND LMIC	2,200	Popoola, Possible Okikiola, et al. "Integrating One Health Approaches into AMR Global Surveillance and Control." *Asian Journal of Medicine and Health* 23.9 (2025): 43-53. Perrella, Alessandro, et al. "From Guidelines to Real-Time Guardrails: The Emerging Role of AI in AMR Surveillance and IPC Decision-Making." (2025).
11/05/2025	Google Scholar	AMR AND silo	5,470	Only duplicates retrieved
11/05/2025	MacOdrum Library	AMR AND AI AND Africa	20	Sartorius, Benn, et al. "The burden of bacterial antimicrobial resistance in the WHO African region in 2019: a cross-country systematic analysis." *The Lancet Global Health* 12.2 (2024): e201-e216.
11/05/2025	MacOdrum Library	AMR AND AI AND LMIC	10	